Confidence in Education

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This document aims to explores the relationship between confidence in the US education system and actual government spending on education.

Loading Packages and Data

In this section, we pull in data downloaded from the Bureau of Economic Analysis (BEA) website and from the General Social Survey (GSS).

Cleaning data

```r
## BEA NIPA data on education spending
govt <- govt_raw %>%
  select(-1) %>%
  slice(-(1:4)) %>%
  filter(row_number() %in% c(1,3,31)) %>%
  t() %>% as.data.frame() %>%
  slice(-1) %>%
  rename(year = V1, govt = V2, educ = V3) %>%
  mutate(educ = as.numeric(educ),
         govt = as.numeric(govt),
         year = as.numeric(year)) %>%
  mutate(educ_govt = educ / govt)

gdp <- gdp_raw %>%
  select(-1) %>%
  slice(-(1:4)) %>%
  filter(row_number() %in% c(1,3)) %>%
  t() %>% as.data.frame() %>%
  slice(-1) %>%
  rename(year = V1, gdp = V2) %>%
  mutate(year = as.numeric(year),
         gdp  = as.numeric(gdp))

nipa <- govt %>%
  left_join(gdp, by = "year") %>%
  mutate(educ_gdp = educ/gdp)
```

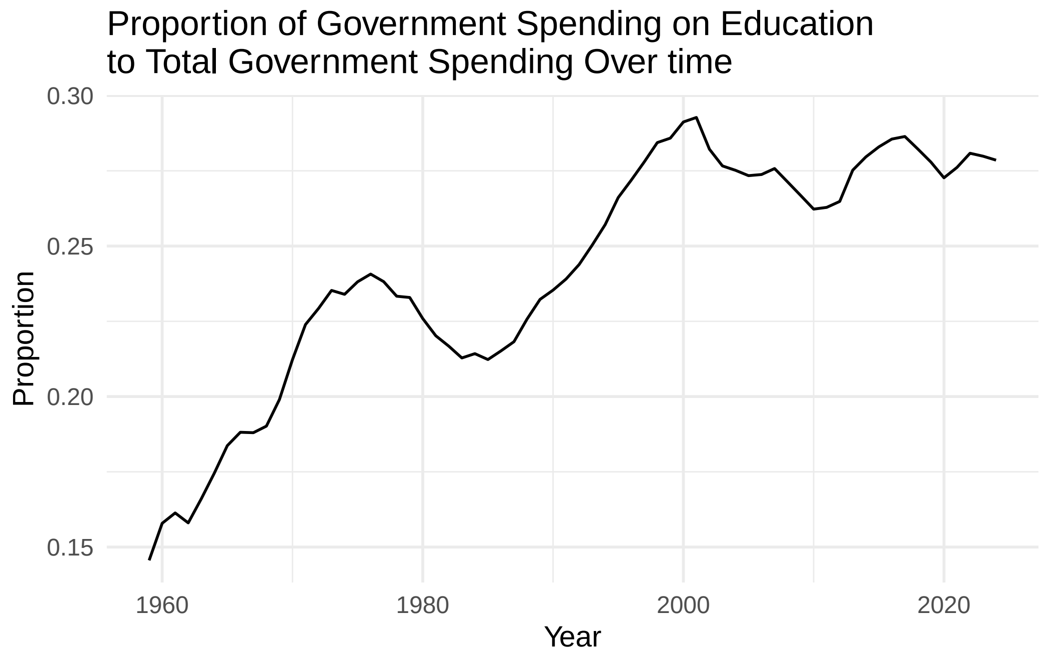
```r
## GSS Education variables
gss_count <- gss_raw %>%
  filter(nateduc %in% c("TOO LITTLE","ABOUT RIGHT","TOO MUCH") &
           coneduc %in% c("A GREAT DEAL","HARDLY ANY","ONLY SOME")) %>%
  select(-id_) %>%
  mutate(year = as.numeric(year))  %>%
  pivot_longer(
    cols = c(nateduc, coneduc),
    names_to = "question",
    values_to = "response"
  ) %>%
```

```r
  group_by(year, question, response) %>%
  summarise(n = n(), .groups = "drop")
```

Analysis

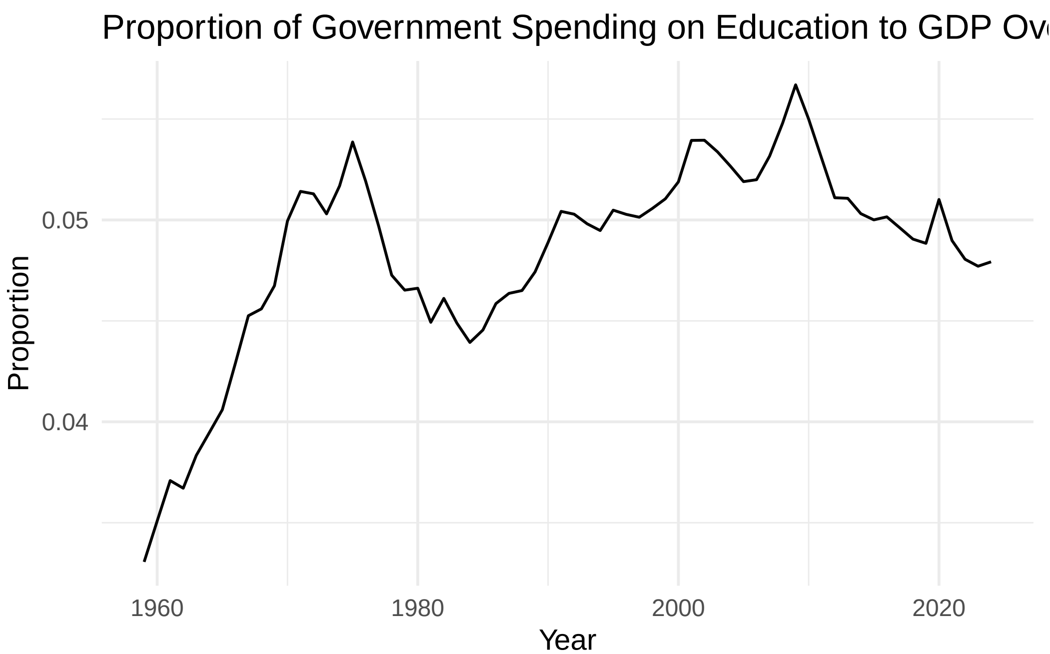
First, lets look at government spending over time in the US. Unfortunately, the BEA's data on inflation adjusted spending only goes back to 2007, which doesn't give us a large sample. As such, we instead use nominal spending on education and divide it by total nominal government spending and by nominal GDP. This proportion gives us insight into how the government is prioritizing spending on education relative to all other spending.

```r
## NIPA Data
ggplot(data = nipa, aes(x=year,y=educ_govt)) +
  geom_line() +
  labs(title="Proportion of Government Spending on Education\nto Total Government Spending
       x = "Year",
       y = "Proportion") +
  theme_minimal()
```



This chart shows that the government has prioritized education more since the 1960s, however this proportion has remained roughly stagnant since the 2000s

```r
ggplot(data = nipa, aes(x=year,y=educ_gdp)) +
  geom_line() +
  labs(title="Proportion of Government Spending on Education to GDP Over time",
       x = "Year",
       y = "Proportion") +
  theme_minimal()
```



This chart shows us that spending on education relative to the total output of the economy increased rapidlyin the 1960s, but has remained somewhat stagnant since the 1970s.

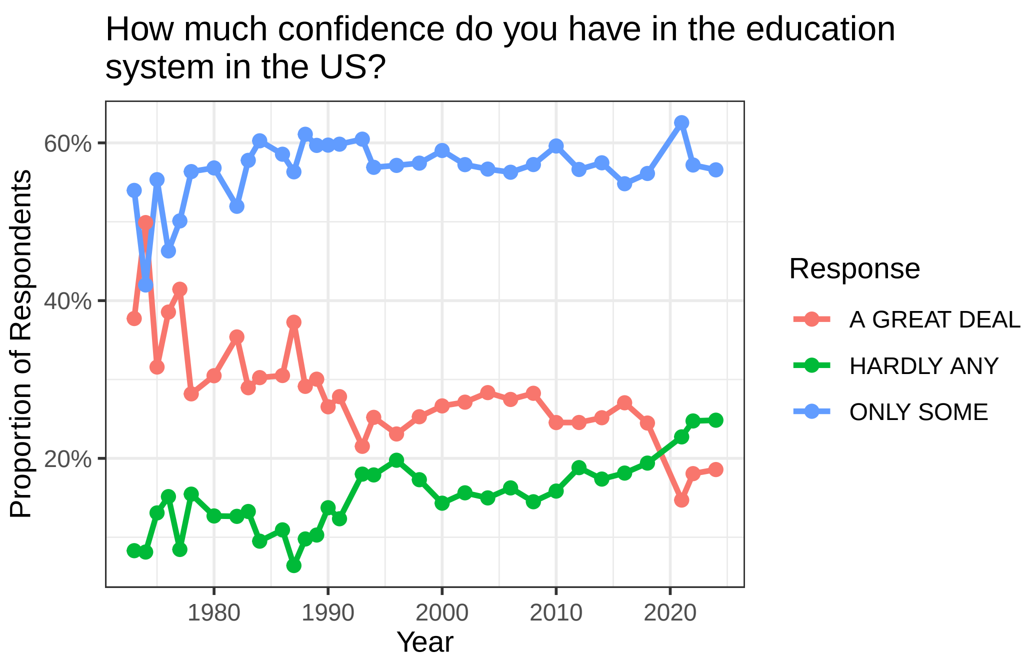
Now that we've seen how spending has changed over time, lets look at confidence in education. The GSS has two surveys that are helpful to us.

- The *coneduc* survey asks whether the respondent has a great deal of confidence, only some confidence, or hardly any confidence in the institution of education in the US.
- The *nateduc* survey asks if the respondent thinks the US government is spending too much, too little, or the right amount on education.

Let's look at how survey responses for each survey have evolved over time with some line charts.

```r
## GSS Data
gss_prop <- gss_count %>%
```

```r
  group_by(year, question) %>%
  mutate(prop = n / sum(n))

# Confidence in Education
coneduc_prop <- gss_prop %>%
  filter(question == "coneduc")

ggplot(coneduc_prop, aes(x = year, y = prop, color = response)) +
  geom_line(linewidth = 1) +
  geom_point(size = 2) +
  scale_y_continuous(labels = scales::percent_format()) +
  labs(
    title = "How much confidence do you have in the education\nsystem in the US?",
    x = "Year",
    y = "Proportion of Respondents",
    color = "Response"
  ) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 0, vjust = 0.5))
```



It appears that confidence in the education system has decreased over time. The proportion of respondents who have a great deal of confidence has decreased from around 40% to less than 20% and the proportion who have hardly any confidence has increased from less than 10% to around 25%.

We can also perform a chi-squared test for independence to test if the distribution of GSS responses is different between two time periods. The hypotheses are:

H_0 : The distribution of responses to how much confidence in education is the same prior to 1990 vs after 1990.

H_a : The distribution of responses is not the same prior to 1990 vs after 1990.

```
# Choose two periods for comparison (example: early vs recent)
gss_test1 <- gss_raw %>%
  filter(coneduc %in% c("HARDLY ANY","ONLY SOME","A GREAT DEAL")) %>%
  mutate(period = ifelse(year <= 1990, "Early", "Late")) %>%
  group_by(period, coneduc) %>%
  summarise(n = n(), .groups = "drop") %>%
  pivot_wider(names_from = coneduc, values_from = n)

gss_test1
```

```
# A tibble: 2 x 4
  period `A GREAT DEAL` `HARDLY ANY` `ONLY SOME`
  <chr>           <int>        <int>       <int>
1 Early            7076         2366       11313
2 Late             7206         5488       17115
```

```
# Run the chi-square test
chisq.test(gss_test1[ , -1])
```

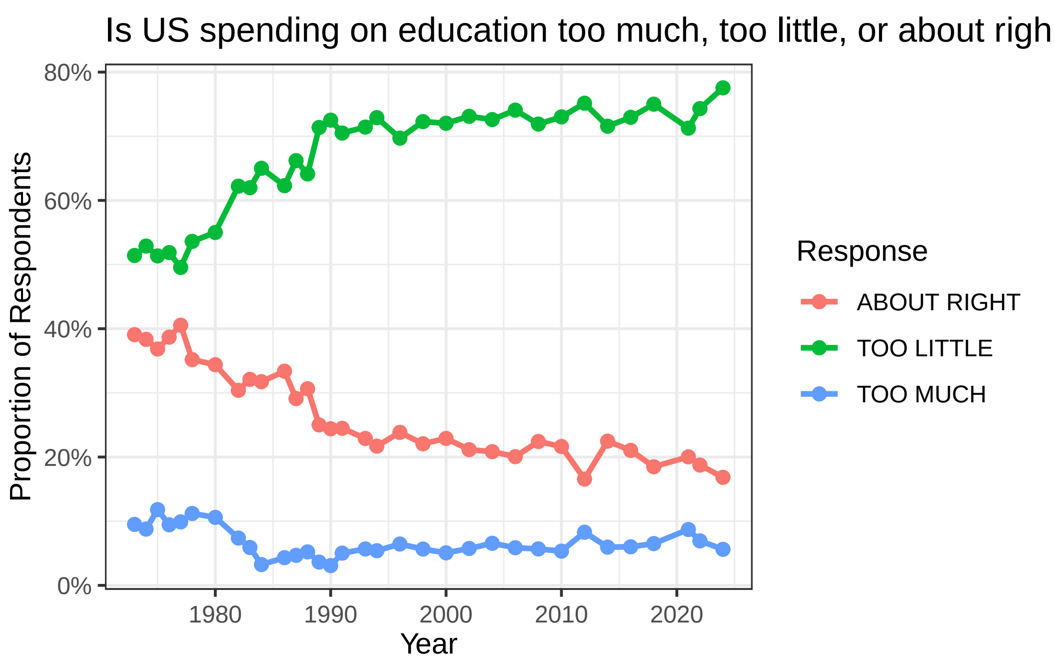
```

	Pearson's Chi-squared test

data:  gss_test1[, -1]
X-squared = 831.81, df = 2, p-value < 2.2e-16
```

Since the p-value is less than 0.05, we can reject the null hypothesis at the 5% level. In other words, we have sufficient statistical evidence to conclude that the distribution of responses is different prior to 1990 vs after 1990.

What about feelings about education spending?

```
# Spending on Education
nateduc_prop <- gss_prop %>%
```

```
  filter(question == "nateduc")

ggplot(nateduc_prop, aes(x = year, y = prop, color = response)) +
  geom_line(linewidth = 1) +
  geom_point(size = 2) +
  scale_y_continuous(labels = scales::percent_format()) +
  labs(
    title = "Is US spending on education too much, too little, or about right?",
    x = "Year",
    y = "Proportion of Respondents",
    color = "Response"
  ) +
  theme_bw() +
  theme(axis.text.x = element_text(angle = 0, vjust = 0.5))
```



Since the beginning of the survey, most respondents believed that the government was spending too little on education, and this proportion has increased significantly to almost 80% of respondents.

We can also perform a chi-squared test for independence to test if the distribution of GSS responses is different between two time periods. The hypothese are:

H_0 : The distribution of responses to how much are we spending on education is the same prior to 1990 vs after 1990.

H_a : The distribution of responses is not the same prior to 1990 vs after 1990.

```
# Choose two periods for comparison (example: early vs recent)
gss_test2 <- gss_raw %>%
  filter(nateduc %in% c("TOO LITTLE","ABOUT RIGHT","TOO MUCH")) %>%
  mutate(period = ifelse(year <= 1990, "Early", "Late")) %>%
  group_by(period, nateduc) %>%
  summarise(n = n(), .groups = "drop") %>%
  pivot_wider(names_from = nateduc, values_from = n)

gss_test2
```

```
# A tibble: 2 x 4
  period `ABOUT RIGHT` `TOO LITTLE` `TOO MUCH`
  <chr>          <int>        <int>      <int>
1 Early           6183        10351       1440
2 Late            4989        17102       1432
```

```
# Run the chi-square test
chisq.test(gss_test2[ , -1])
```

```
    Pearson's Chi-squared test

data:  gss_test2[, -1]
X-squared = 1064.8, df = 2, p-value < 2.2e-16
```

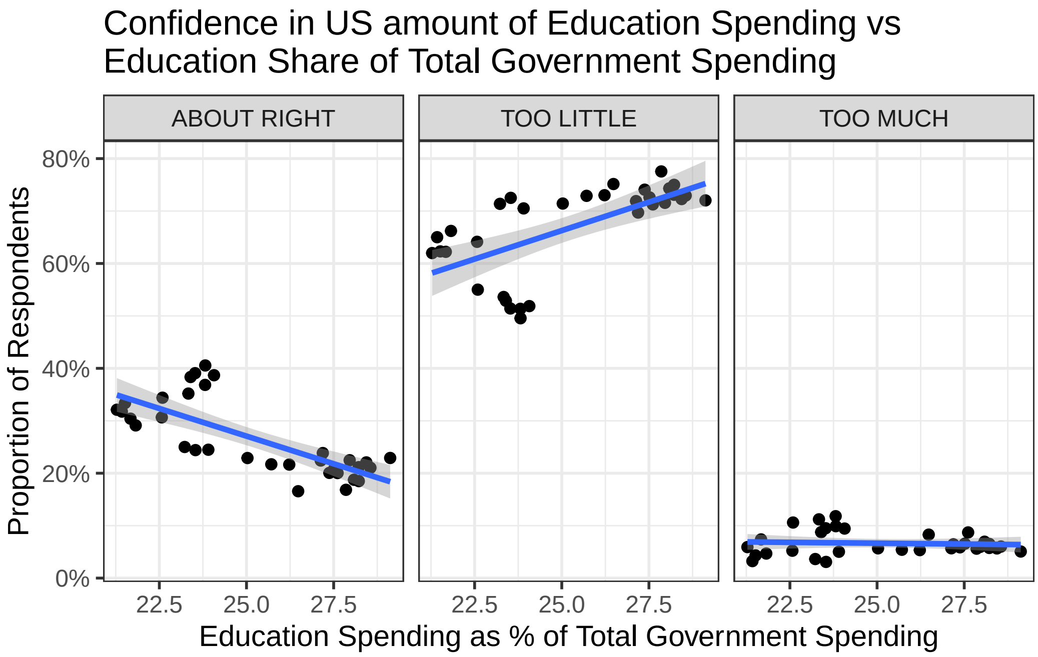
Again, since the p-value is less than 0.05, we can reject the null hypothesis at the 5% level. In other words, we have sufficient statistical evidence to conclude that the distribution of responses is different prior to 1990 vs after 1990.

Now lets investigate how spending and confidence in education relate to each other. The following charts show how opinions about the amount of education spending relate to education spending as a percent of total government spending and GDP.

```
nateduc_nipa <- gss_prop %>%
  filter(question == "nateduc") %>%
  left_join(nipa, by = "year")

ggplot(nateduc_nipa, aes(x = 100*educ_govt, y = prop)) +
  geom_point() +
  geom_smooth(method = "lm") +
```

```
  facet_wrap(~ response) +
  labs(
    title = "Confidence in US amount of Education Spending vs\nEducation Share of Total Go
    x = "Education Spending as % of Total Government Spending",
    y = "Proportion of Respondents"
  ) +
  scale_y_continuous(labels = scales::percent) +
  theme_bw()
```

```
`geom_smooth()` using formula = 'y ~ x'
```

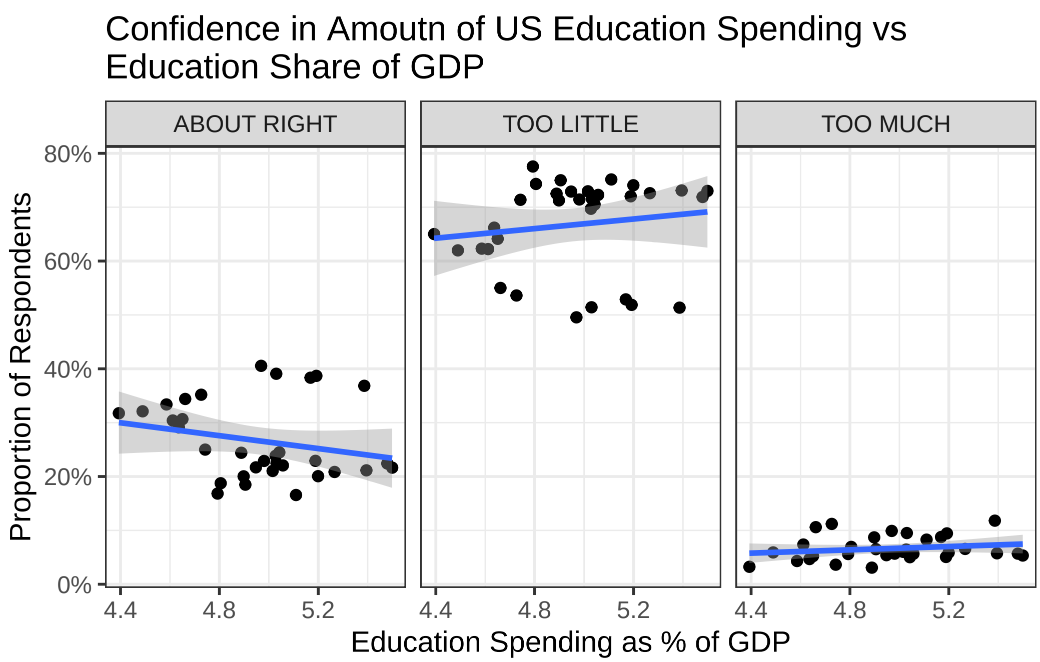


The negative slope for the respondents who believe the government spends about the right amount on education and the positive slope for the those who believe the government spends too little on education indicate that even when the government prioritize education more, people still believe that the government isn't spending enough. This may indicate that despite some efforts to spend more, the government still isn't spending as much on education as they should.

```
ggplot(nateduc_nipa, aes(x = 100*educ_gdp, y = prop)) +
  geom_point() +
  geom_smooth(method = "lm") +
  facet_wrap(~ response) +
```

```r
  labs(
    title = "Confidence in Amoutn of US Education Spending vs\nEducation Share of GDP",
    x = "Education Spending as % of GDP",
    y = "Proportion of Respondents"
  ) +
  scale_y_continuous(labels = scales::percent) +
  theme_bw()
```

```
`geom_smooth()` using formula = 'y ~ x'
```



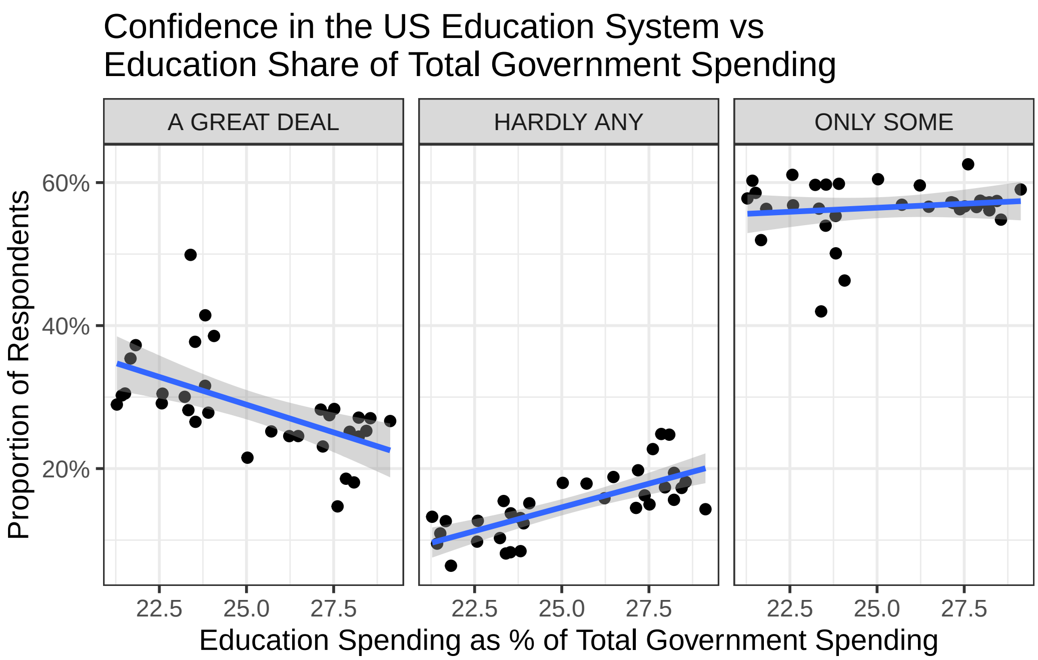
This chart shows the same relationship as the previous, although to a lesser extent. This further reinforces that the people demand even more spending on education.

Doing the same with confidence in the education system gives similar results.

```r
coneduc_nipa <- gss_prop %>%
  filter(question == "coneduc") %>%
  left_join(nipa, by = "year")

ggplot(coneduc_nipa, aes(x = 100*educ_govt, y = prop)) +
  geom_point() +
  geom_smooth(method = "lm") +
```

```
  facet_wrap(~ response) +
  labs(
    title = "Confidence in the US Education System vs\nEducation Share of Total Government
    x = "Education Spending as % of Total Government Spending",
    y = "Proportion of Respondents"
  ) +
  scale_y_continuous(labels = scales::percent) +
  theme_bw()
```

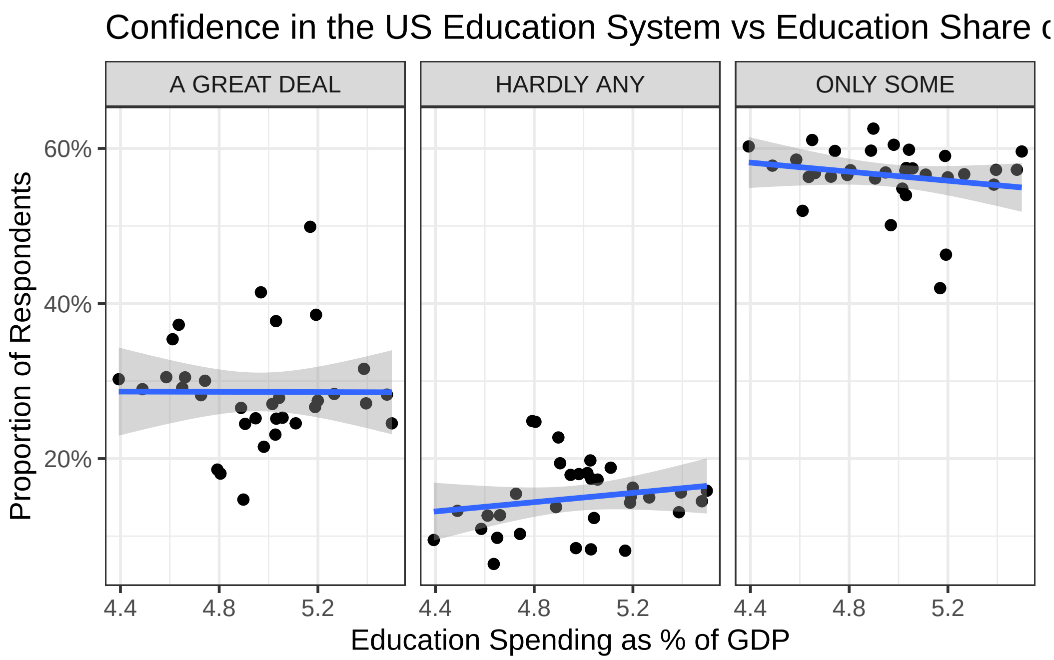
```
`geom_smooth()` using formula = 'y ~ x'
```




```
ggplot(coneduc_nipa, aes(x = 100*educ_gdp, y = prop)) +
  geom_point() +
  geom_smooth(method = "lm") +
  facet_wrap(~ response) +
  labs(
    title = "Confidence in the US Education System vs Education Share of GDP",
    x = "Education Spending as % of GDP",
    y = "Proportion of Respondents"
  ) +
  scale_y_continuous(labels = scales::percent) +
```

```
    theme_bw()
```

```
`geom_smooth()` using formula = 'y ~ x'
```



Even as government spending on increases, people still increasingly have lost trust in the education system in the US.

ARIMA

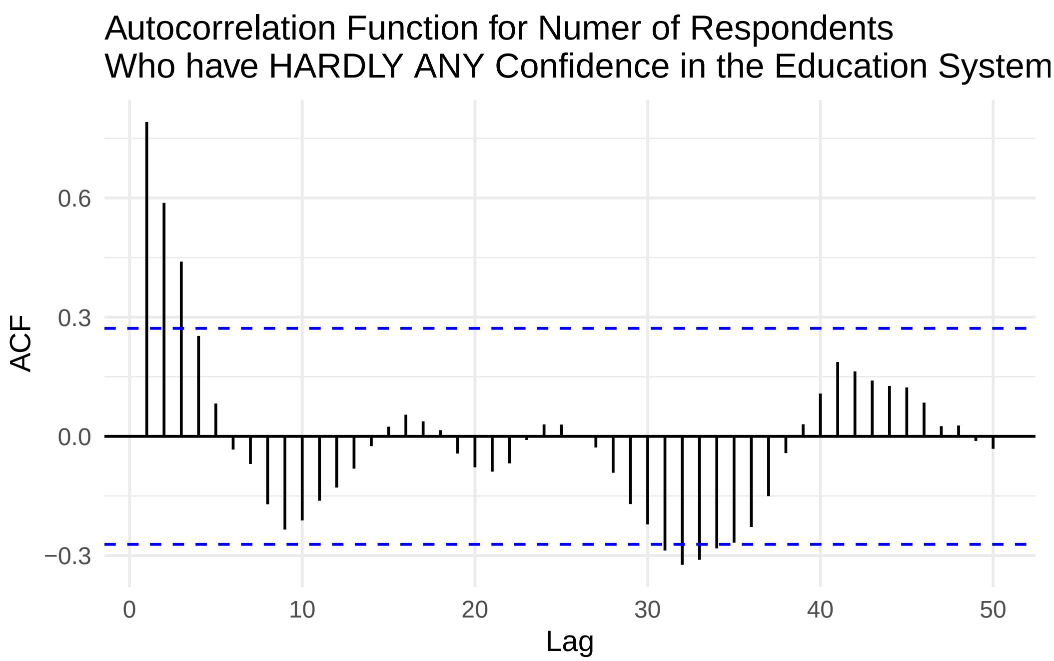
In this section, we analyze and attempt to forecast the time series for confidence in education and education spending.

Educational Confidence

First lets check for stationarity.

```
coneduc_ts_df <- coneduc_prop %>%
  ungroup () %>%
  filter(response == "HARDLY ANY") %>%
  select(year,n) %>%
```

```
  arrange(year) %>%
  complete(year = full_seq(year, 1)) %>%
  mutate(n = na.approx(n, year, na.rm = FALSE))

coneduc_ts <- ts(coneduc_ts_df$n,
                 start = min(coneduc_ts_df$year),
                 end   = max(coneduc_ts_df$year),
                 frequency = 1)

ggAcf(coneduc_ts, 50) +
  ggtitle("Autocorrelation Function for Numer of Respondents\nWho have HARDLY ANY Confiden
  theme_minimal()
```



This plot shows clear autocorrleation. Lets confirm stationarity with an augmented Dickey Fuller test.

```
tseries::adf.test(coneduc_ts)
```

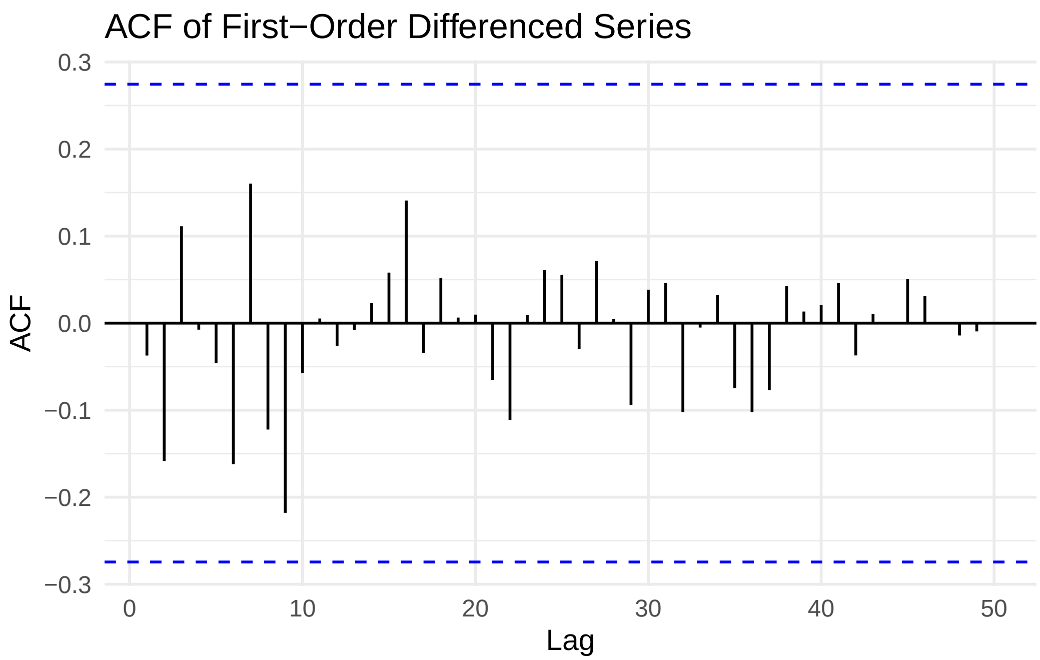
```

	Augmented Dickey-Fuller Test

data:  coneduc_ts
Dickey-Fuller = -2.1032, Lag order = 3, p-value = 0.5329
```

```
alternative hypothesis: stationary
```

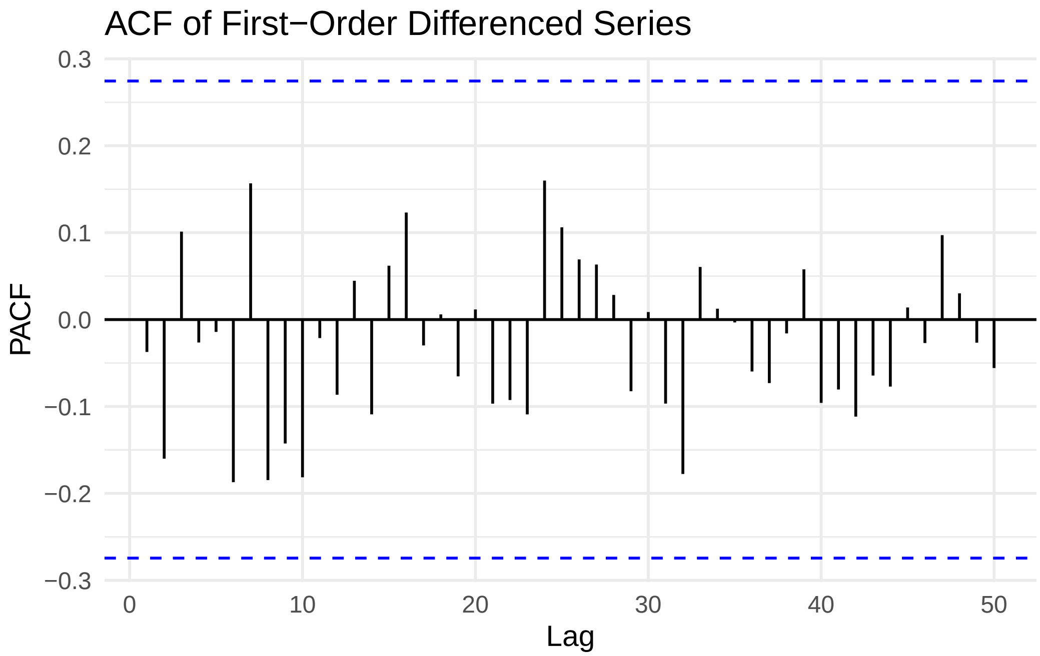
Because the p-values for this test is greater than 0.05, we cannot reject the null hypothesis that these series are not stationary.

Lets try to correct this with differencing.

```
diff_1 <- diff(coneduc_ts)
ggAcf(diff_1,50) +
  ggtitle("ACF of First-Order Differenced Series") +
  theme_minimal()
```




```
ggPacf(diff_1,50) +
  ggtitle("ACF of First-Order Differenced Series") +
  theme_minimal()
```



The ACF and PACF plots for the differenced series indicate that the data is now stationary and does not need additional differencing.

Now that we know that one difference is necessary, lets move on to a parameter search.

```
# Define parameter ranges
p_range <- 0:7
d_range <- 1
q_range <- 0:9

# Calculate total combinations
n_combinations <- length(p_range) * length(d_range) * length(q_range)

# Create an empty matrix to store results
results_matrix <- matrix(NA, nrow = n_combinations, ncol = 6)

# Initialize index for matrix row
i <- 1

# Loop through combinations of ARIMA model parameters
for (q in q_range) {
  for (p in p_range) {
    d <- d_range
```

```r
    # Fit ARIMA model with specified (p,d,q)
    model <- Arima(coneduc_ts, order = c(p, d, q), include.drift = TRUE)

    # Store model parameters and AIC/BIC/AICc values in matrix
    results_matrix[i, ] <- c(p, d, q, model$aic, model$bic, model$aicc)

    # Increment row index
    i <- i + 1
  }
}

# Convert matrix to data frame
results_df <- as.data.frame(results_matrix)
colnames(results_df) <- c("p", "d", "q", "AIC", "BIC", "AICc")

# Find the row with the lowest AIC
highlight_row <- which.min(results_df$AIC)

# Generate kable table with highlighting for the row with the lowest AIC
knitr::kable(results_df, align = 'c', caption = "Comparison of ARIMA Models") %>%
  kable_styling(full_width = FALSE, position = "center") %>%
  row_spec(highlight_row, bold = TRUE, background = "#FFFF99")  # Highlight row in yellow
```

Table 1: Comparison of ARIMA Models

p	d	q	AIC	BIC	AICc
0	**1**	**0**	**523.9316**	**527.7952**	**524.1816**
1	1	0	525.8619	531.6574	526.3726
2	1	0	526.5106	534.2379	527.3801
3	1	0	528.0177	537.6768	529.3510
4	1	0	530.0047	541.5956	531.9138
5	1	0	531.9476	545.4703	534.5522
6	1	0	531.7974	547.2520	535.2260
7	1	0	531.3935	548.7799	535.7837
0	1	1	525.8318	531.6273	526.3424
1	1	1	525.3456	533.0729	526.2152
2	1	1	525.7551	535.4143	527.0885
3	1	1	527.7517	539.3426	529.6608
4	1	1	529.6103	543.1331	532.2149
5	1	1	530.7139	546.1685	534.1425

6	1	1	529.3822	546.7686	533.7724
7	1	1	531.0506	550.3688	536.5506
0	1	2	526.4794	534.2067	527.3489
1	1	2	525.8172	535.4763	527.1505
2	1	2	525.6421	537.2330	527.5512
3	1	2	527.6585	541.1813	530.2631
4	1	2	529.1759	544.6305	532.6045
5	1	2	531.0983	548.4847	535.4886
6	1	2	529.7733	549.0916	535.2733
7	1	2	533.0414	554.2915	539.8106
0	1	3	527.4734	537.1325	528.8067
1	1	3	527.7753	539.3663	529.6844
2	1	3	529.4382	542.9610	532.0429
3	1	3	528.5947	544.0493	532.0233
4	1	3	533.7515	551.1379	538.1417
5	1	3	535.7514	555.0697	541.2514
6	1	3	530.4987	551.7488	537.2679
7	1	3	532.2031	555.3850	540.4136
0	1	4	528.0980	539.6890	530.0071
1	1	4	527.7946	541.3173	530.3992
2	1	4	529.1797	544.6344	532.6083
3	1	4	529.5575	546.9439	533.9477
4	1	4	530.0836	549.4019	535.5836
5	1	4	532.0574	553.3075	538.8266
6	1	4	531.7642	554.9461	539.9748
7	1	4	533.7488	558.8625	543.5866
0	1	5	529.9532	543.4760	532.5579
1	1	5	529.5092	544.9638	532.9378
2	1	5	530.9767	548.3632	535.3670
3	1	5	531.5131	550.8314	537.0131
4	1	5	531.9258	553.1759	538.6950
5	1	5	533.2169	556.3988	541.4274
6	1	5	533.7913	558.9051	543.6292
7	1	5	534.8762	561.9217	546.5429
0	1	6	528.8009	544.2556	532.2295
1	1	6	530.4620	547.8484	534.8523
2	1	6	531.3567	550.6749	536.8567
3	1	6	531.7473	552.9974	538.5165
4	1	6	533.6516	556.8336	541.8622

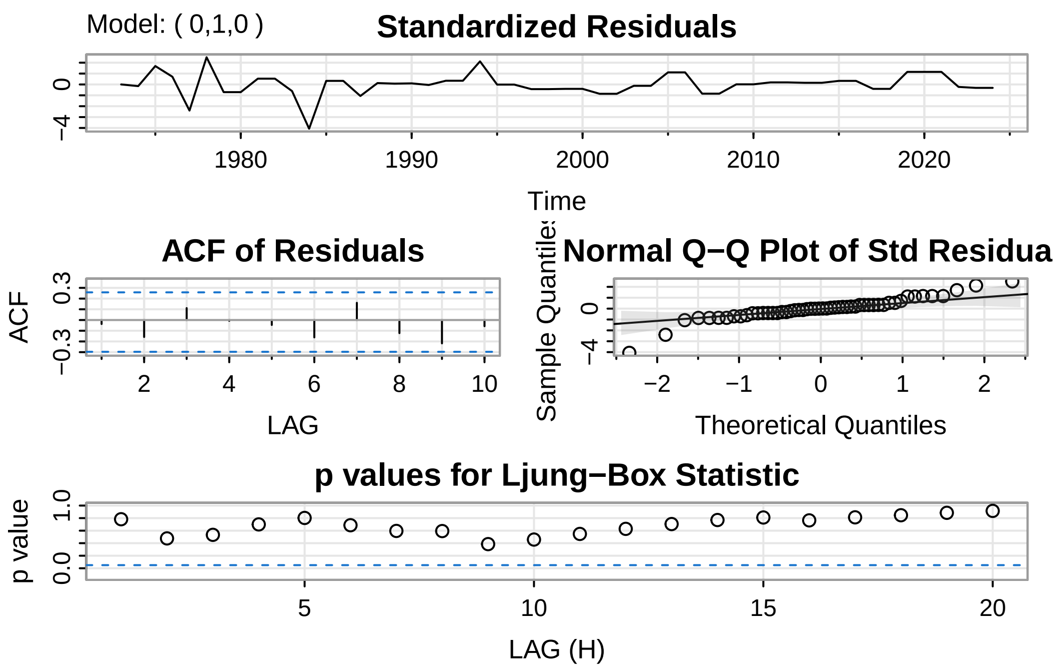
5	1	6	532.5296	557.6434	542.3675
6	1	6	534.4466	561.4921	546.1132
7	1	6	536.3219	565.2993	550.0362
0	1	7	530.5263	547.9127	534.9165
1	1	7	532.4381	551.7564	537.9381
2	1	7	531.5964	552.8464	538.3656
3	1	7	533.6102	556.7921	541.8207
4	1	7	535.6055	560.7193	545.4434
5	1	7	534.3078	561.3533	545.9745
6	1	7	536.4084	565.3858	550.1227
7	1	7	538.3224	569.2316	554.3224
0	1	8	531.5503	550.8686	537.0503
1	1	8	530.7664	552.0165	537.5356
2	1	8	531.0827	554.2647	539.2933
3	1	8	532.0008	557.1146	541.8387
4	1	8	532.7487	559.7942	544.4153
5	1	8	536.0547	565.0321	549.7690
6	1	8	534.7608	565.6700	550.7608
7	1	8	535.5688	568.4099	554.1143
0	1	9	527.4698	548.7199	534.2391
1	1	9	529.4452	552.6271	537.6557
2	1	9	530.8564	555.9701	540.6942
3	1	9	532.7977	559.8433	544.4644
4	1	9	534.6063	563.5837	548.3206
5	1	9	536.5233	567.4326	552.5233
6	1	9	534.7177	567.5587	553.2631
7	1	9	536.7107	571.4836	558.0857

```
auto.arima(coneduc_ts)
```

```
Series: coneduc_ts
ARIMA(0,1,0)

sigma^2 = 1576:  log likelihood = -260.11
AIC=522.22   AICc=522.31   BIC=524.16
```

According to the parameter search and the auto.arima() function, our best model is a simple ARIMA(0,1,0). Lets quickly look at the model diagnostics.

```r
model_output1 <- capture.output(sarima(coneduc_ts, 0, 1, 0))
```




```r
# Find the line numbers dynamically based on a keyword
start_line <- grep("Coefficients", model_output1)  # Locate where coefficient details star
end_line <- length(model_output1)  # Last line of output

# Print the relevant section automatically
cat(model_output1[start_line:end_line], sep = "\n")
```

```
Coefficients:
         Estimate     SE t.value p.value
constant        3 5.5429  0.5412  0.5908

sigma^2 estimated as 1566.908 on 50 degrees of freedom

AIC = 10.27317  AICc = 10.27477  BIC = 10.34893
```

The **Residual Plot** shows nearly consistent fluctuation around zero, suggesting that the residuals are nearly stationary with a constant mean and finite variance over time.

The **Autocorrelation Function (ACF)** of the residuals reveals no significant autocorrelations.

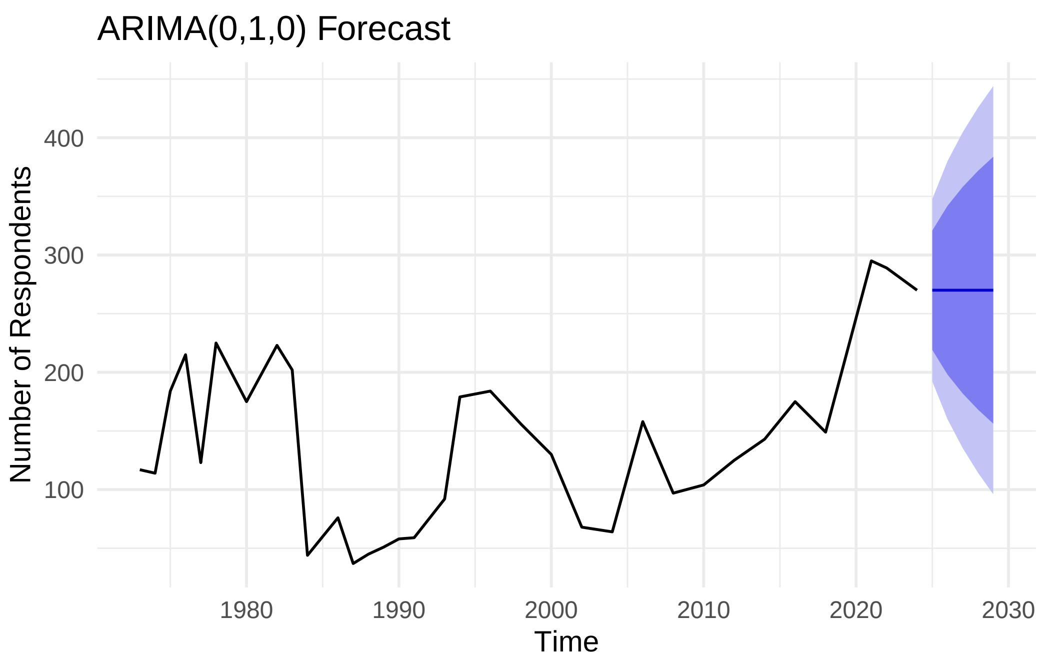
The **Q-Q Plot** indicates that the residuals follow a near-normal distribution, with minor deviations at the tails, which is typical in time series data.

The **Ljung-Box Test** p-values remain above the 0.05 significance level, implying no significant autocorrelations left in the residuals.

```r
fit <- Arima(coneduc_ts, order = c(0,1,0), include.drift = FALSE)
summary(fit)
```

```
Series: coneduc_ts
ARIMA(0,1,0)

sigma^2 = 1576:  log likelihood = -260.11
AIC=522.22   AICc=522.31   BIC=524.16

Training set error measures:
                   ME     RMSE      MAE       MPE     MAPE      MASE
Training set 2.944558 39.31416 25.82917 -5.521189 24.46233 0.9808547
                    ACF1
Training set -0.03702793
```

```r
# Generate the forecast
forecast_result <- forecast(fit, h = 5)

# Plot the forecast
autoplot(forecast_result) +
  labs(title = "ARIMA(0,1,0) Forecast",
       x = "Time",
       y = "Number of Respondents") +
  theme_minimal()
```

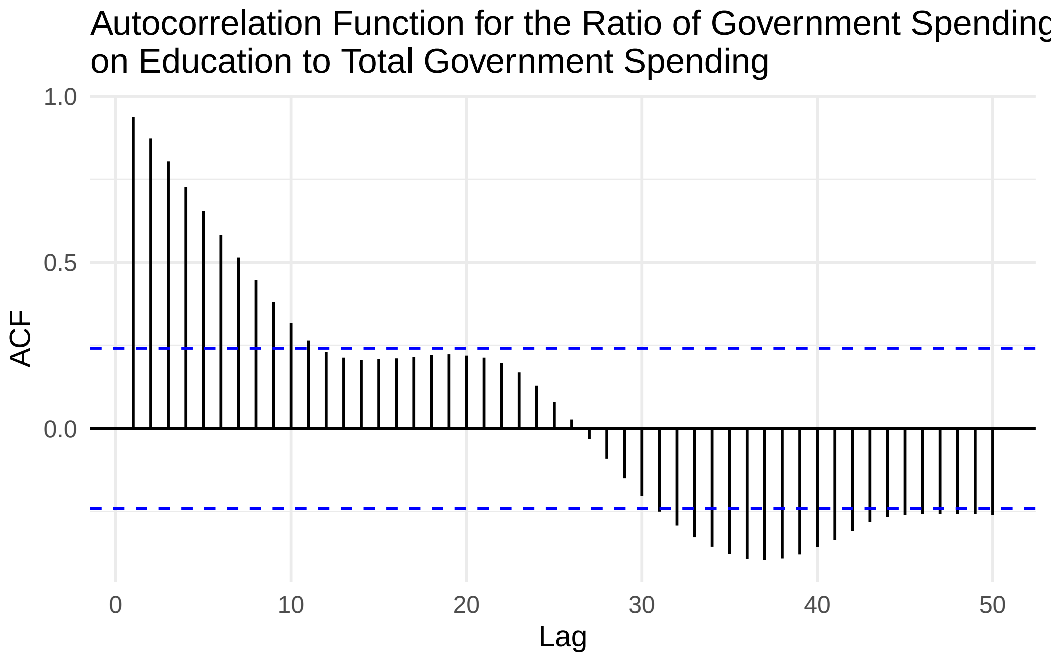


The ARIMA predicts that confidence in education will remain low over time.

Government Spending on Education

We can also do the same for the ratio of government spending on education to total government spending

```
govt_ratio_ts <- ts(nipa$educ_govt,
                    start = min(nipa$year),
                    end   = max(nipa$year),
                    frequency = 1)

ggAcf(govt_ratio_ts, 50) +
  ggtitle("Autocorrelation Function for the Ratio of Government Spending\non Education to
  theme_minimal()
```



This plot shows clear autocorrleation. Lets confirm stationarity with an augmented Dickey Fuller test.

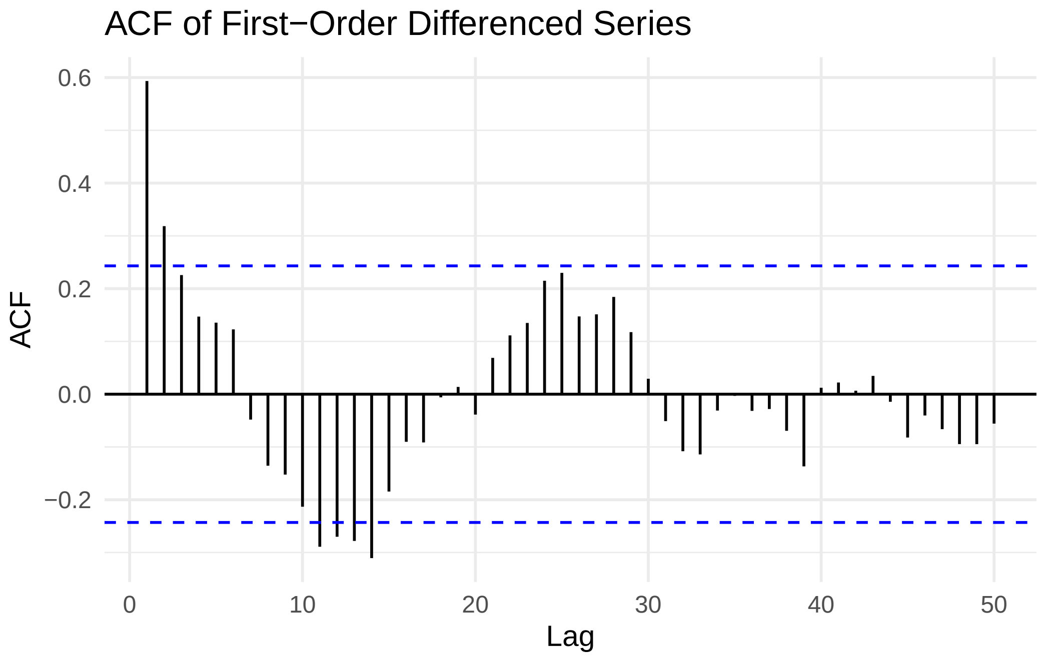
```
tseries::adf.test(govt_ratio_ts)
```

```

	Augmented Dickey-Fuller Test

data:  govt_ratio_ts
Dickey-Fuller = -2.6035, Lag order = 4, p-value = 0.3302
alternative hypothesis: stationary
```

Because the p-values for this test is greater than 0.05, we cannot reject the null hypothesis that these series are not stationary.

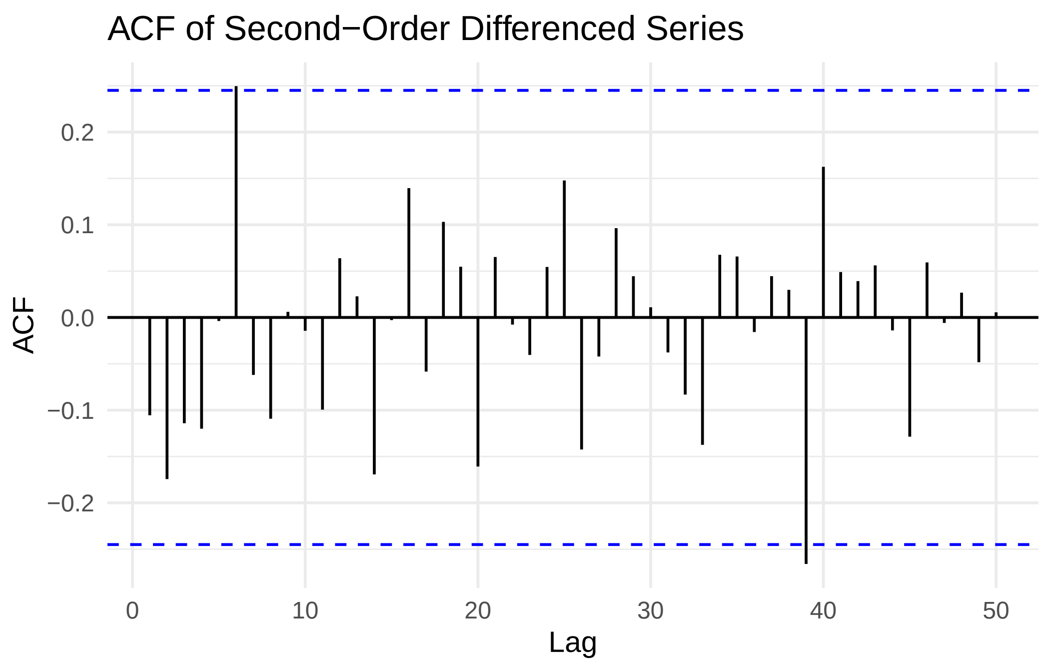
Lets try to correct this with differencing.

```
diff_1 <- diff(govt_ratio_ts)
ggAcf(diff_1,50) +
  ggtitle("ACF of First-Order Differenced Series") +
  theme_minimal()
```

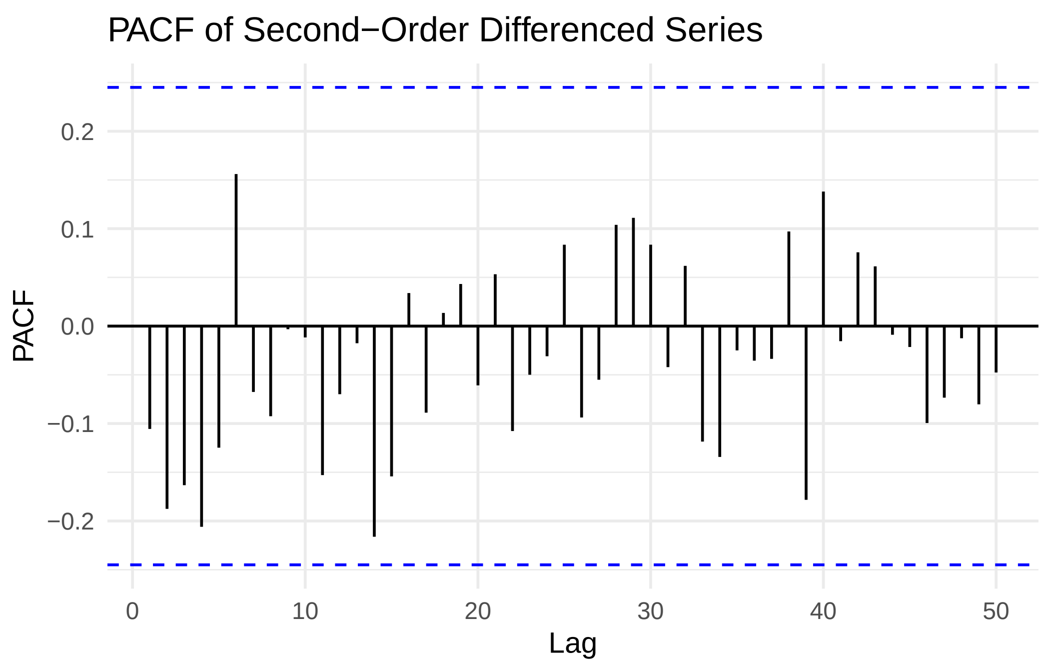


It appears that one round of differencing potentially wasn't sufficient so lets try again.

```
diff_2 <- diff(govt_ratio_ts, differences = 2)
ggAcf(diff_2,50) +
  ggtitle("ACF of Second-Order Differenced Series") +
  theme_minimal()
```




```r
ggPacf(diff_2,50) +
  ggtitle("PACF of Second-Order Differenced Series") +
  theme_minimal()
```



This plot looks much better. With this, we can proceed with the ARIMA.

First lets find the optimal parameters

```r
# Define parameter ranges
p_range <- 0:6
d_range <- 2
q_range <- 0:6

# Calculate total combinations
n_combinations <- length(p_range) * length(d_range) * length(q_range)

# Create an empty matrix to store results
results_matrix <- matrix(NA, nrow = n_combinations, ncol = 6)

# Initialize index for matrix row
i <- 1

# Loop through combinations of ARIMA model parameters
for (q in q_range) {
  for (p in p_range) {
    d <- d_range

    # Fit ARIMA model with specified (p,d,q)
    model <- Arima(govt_ratio_ts, order = c(p, d, q), include.drift = TRUE)

    # Store model parameters and AIC/BIC/AICc values in matrix
    results_matrix[i, ] <- c(p, d, q, model$aic, model$bic, model$aicc)

    # Increment row index
    i <- i + 1
  }
}

# Convert matrix to data frame
results_df <- as.data.frame(results_matrix)
colnames(results_df) <- c("p", "d", "q", "AIC", "BIC", "AICc")

# Find the row with the lowest AIC
highlight_row <- which.min(results_df$AIC)

# Generate kable table with highlighting for the row with the lowest AIC
```

```r
knitr::kable(results_df, align = 'c', caption = "Comparison of ARIMA Models") %>%
  kable_styling(full_width = FALSE, position = "center") %>%
  row_spec(highlight_row, bold = TRUE, background = "#FFFF99")  # Highlight row in yellow
```

Table 2: Comparison of ARIMA Models

p	d	q	AIC	BIC	AICc
0	2	0	-509.1450	-506.9862	-509.0805
1	2	0	-507.8822	-503.5644	-507.6854
2	2	0	-508.6508	-502.1741	-508.2508
3	2	0	-508.5182	-499.8827	-507.8403
4	2	0	-509.3132	-498.5188	-508.2787
5	2	0	-508.2068	-495.2535	-506.7331
6	2	0	-508.7396	-493.6275	-506.7396
0	2	1	-508.5359	-504.2181	-508.3392
1	**2**	**1**	**-514.1772**	**-507.7005**	**-513.7772**
2	2	1	-512.6025	-503.9669	-511.9245
3	2	1	-510.7744	-499.9800	-509.7399
4	2	1	-507.6409	-494.6876	-506.1673
5	2	1	-507.6379	-492.5257	-505.6379
6	2	1	-506.8387	-489.5676	-504.2205
0	2	2	-511.8847	-505.4080	-511.4847
1	2	2	-512.6647	-504.0292	-511.9868
2	2	2	-510.7008	-499.9064	-509.6663
3	2	2	-508.9996	-496.0463	-507.5260
4	2	2	-507.4921	-492.3799	-505.4921
5	2	2	-510.9493	-493.6782	-508.3311
6	2	2	-509.4328	-490.0028	-506.0994
0	2	3	-511.3328	-502.6972	-510.6548
1	2	3	-510.7780	-499.9836	-509.7435
2	2	3	-509.3573	-496.4040	-507.8836
3	2	3	-509.4284	-494.3163	-507.4284
4	2	3	-509.6660	-492.3949	-507.0478
5	2	3	-509.3635	-489.9335	-506.0301
6	2	3	-509.9396	-488.3507	-505.7886
0	2	4	-510.5909	-499.7965	-509.5564
1	2	4	-508.6112	-495.6579	-507.1375
2	2	4	-511.8755	-496.7634	-509.8755
3	2	4	-510.3767	-493.1056	-507.7585

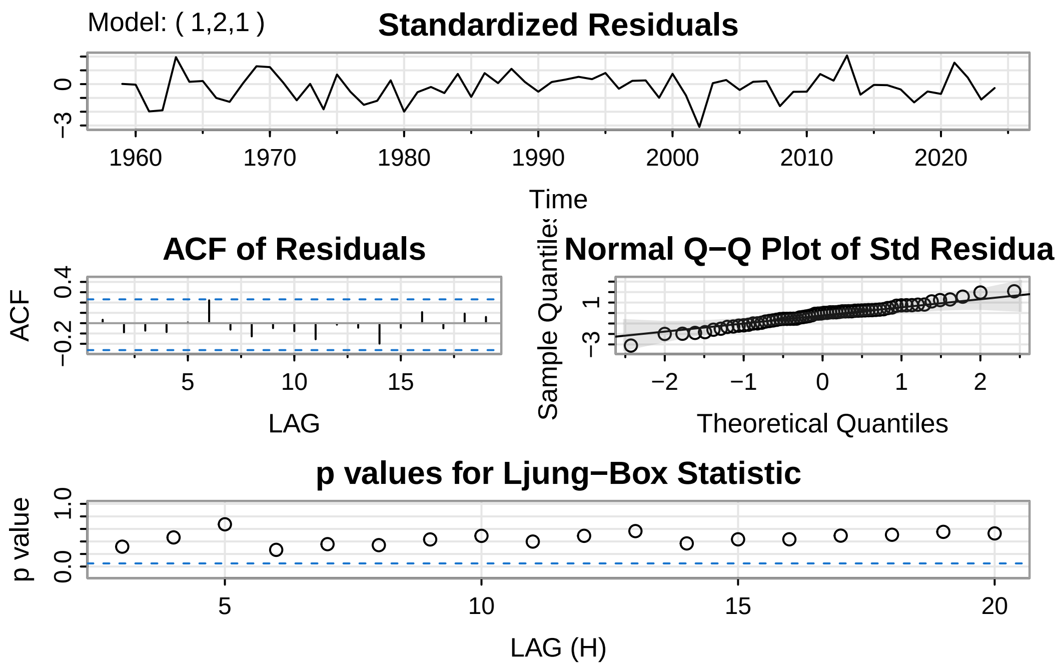
4	2	4	-508.3934	-488.9634	-505.0601
5	2	4	-508.1606	-486.5717	-504.0096
6	2	4	-506.8821	-483.1344	-501.8052
0	2	5	-508.6647	-495.7114	-507.1910
1	2	5	-507.6169	-492.5047	-505.6169
2	2	5	-510.4992	-493.2282	-507.8811
3	2	5	-509.3113	-489.8814	-505.9780
4	2	5	-507.3565	-485.7677	-503.2056
5	2	5	-504.7793	-481.0316	-499.7024
6	2	5	-505.0040	-479.0974	-498.8863
0	2	6	-508.0020	-492.8899	-506.0020
1	2	6	-506.9639	-489.6928	-504.3457
2	2	6	-508.9244	-489.4944	-505.5910
3	2	6	-507.3238	-485.7349	-503.1728
4	2	6	-507.1586	-483.4109	-502.0817
5	2	6	-505.6670	-479.7604	-499.5494
6	2	6	-505.0758	-477.0104	-497.7958

```r
auto.arima(govt_ratio_ts)
```

```
Series: govt_ratio_ts
ARIMA(1,1,0) with drift

Coefficients:
         ar1   drift
      0.6265  0.0022
s.e.  0.0994  0.0013

sigma^2 = 1.688e-05:  log likelihood = 265.68
AIC=-525.37   AICc=-524.98   BIC=-518.85
```

The parameter search suggests an ARIMA(1,2,1) while the auto.arima() suggests ARIMA(1,1,0). Lets compare these.

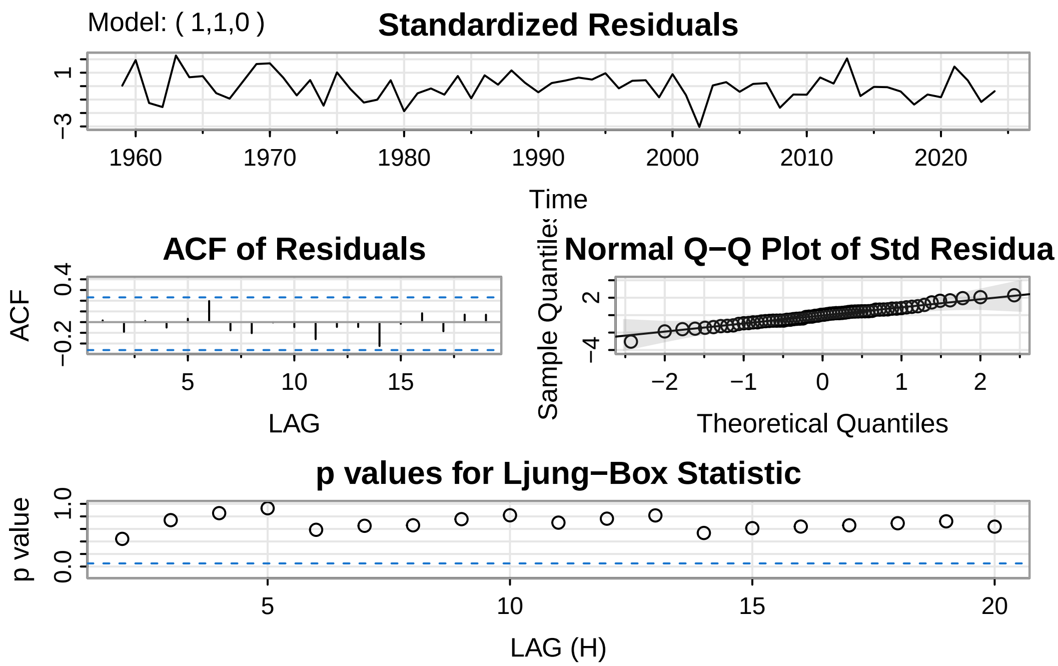
```r
model_output1 <- capture.output(sarima(govt_ratio_ts,1,2,1))
```




```r
# Find the line numbers dynamically based on a keyword
start_line <- grep("Coefficients", model_output1)  # Locate where coefficient details star
end_line <- length(model_output1)  # Last line of output

# Print the relevant section automatically
cat(model_output1[start_line:end_line], sep = "\n")
```

```
Coefficients:
    Estimate     SE  t.value p.value
ar1   0.6331 0.1159   5.4633       0
ma1  -0.9630 0.0606 -15.8968       0

sigma^2 estimated as 1.6952e-05 on 62 degrees of freedom

AIC = -8.034018  AICc = -8.030944  BIC = -7.932821
```

```r
model_output2 <- capture.output(sarima(govt_ratio_ts,1,1,0))
```




```r
# Find the line numbers dynamically based on a keyword
start_line <- grep("Coefficients", model_output2)  # Locate where coefficient details star
end_line <- length(model_output2)  # Last line of output

# Print the relevant section automatically
cat(model_output2[start_line:end_line], sep = "\n")
```

```
Coefficients:
         Estimate     SE t.value p.value
ar1        0.6265 0.0994  6.3024  0.0000
constant   0.0022 0.0013  1.6815  0.0976

sigma^2 estimated as 1.636366e-05 on 63 degrees of freedom

AIC = -8.082595  AICc = -8.079617  BIC = -7.982238
```

Both **Residual Plots** show nearly consistent fluctuation around zero, suggesting that the residuals are nearly stationary with a constant mean and finite variance over time.

Both **Autocorrelation Functions (ACF)** of the residuals reveal very few, if any, significant autocorrelations.

Both **Q-Q Plots** indicate that the residuals follow a near-normal distribution, with minor deviations at the tails, which is typical in time series data.

Both **Ljung-Box Test** p-values remain above the 0.05 significance level, implying no significant autocorrelations left in the residuals.

Coefficient Significance: Most model coefficients are significant for both models. Only the constant in the ARIMA(1,1,0) model is insignificant

```r
fit1 <- Arima(govt_ratio_ts, order = c(1,2,1), include.drift = FALSE)
summary(fit1)
```

```
Series: govt_ratio_ts
ARIMA(1,2,1)

Coefficients:
         ar1      ma1
      0.6331  -0.9630
s.e.  0.1159   0.0606

sigma^2 = 1.75e-05:  log likelihood = 260.09
AIC=-514.18   AICc=-513.78   BIC=-507.7

Training set error measures:
                        ME        RMSE         MAE        MPE     MAPE
Training set -0.0007986968 0.004054478 0.003070733 -0.3479504 1.330397
                  MASE       ACF1
Training set 0.6659165 0.03300224
```

```r
fit2 <- Arima(govt_ratio_ts, order = c(1,1,0), include.drift = TRUE)
summary(fit2)
```

```
Series: govt_ratio_ts
ARIMA(1,1,0) with drift

Coefficients:
         ar1   drift
      0.6265  0.0022
s.e.  0.0994  0.0013

sigma^2 = 1.688e-05:  log likelihood = 265.68
```

```
AIC=-525.37   AICc=-524.98   BIC=-518.85

Training set error measures:
                        ME        RMSE         MAE          MPE    MAPE
Training set -0.0001277292 0.004014478 0.003190882 -0.002967276 1.40237
                  MASE      ACF1
Training set 0.6919718 0.0157504
```

The RMSE is slightly lower in the ARIMA(1,1,0) model, but the MAE is slightly larger.

```
naive <- naive(govt_ratio_ts,h=5)
mean  <- meanf(govt_ratio_ts,h=5)
drift <- rwf(govt_ratio_ts,drift=TRUE,h=5)
accuracy(naive)
```

```
                      ME        RMSE         MAE       MPE    MAPE MASE
Training set 0.002045329 0.005521567 0.004611289 0.9654682 2.00654    1
                  ACF1
Training set 0.5933769
```

```
accuracy(mean)
```

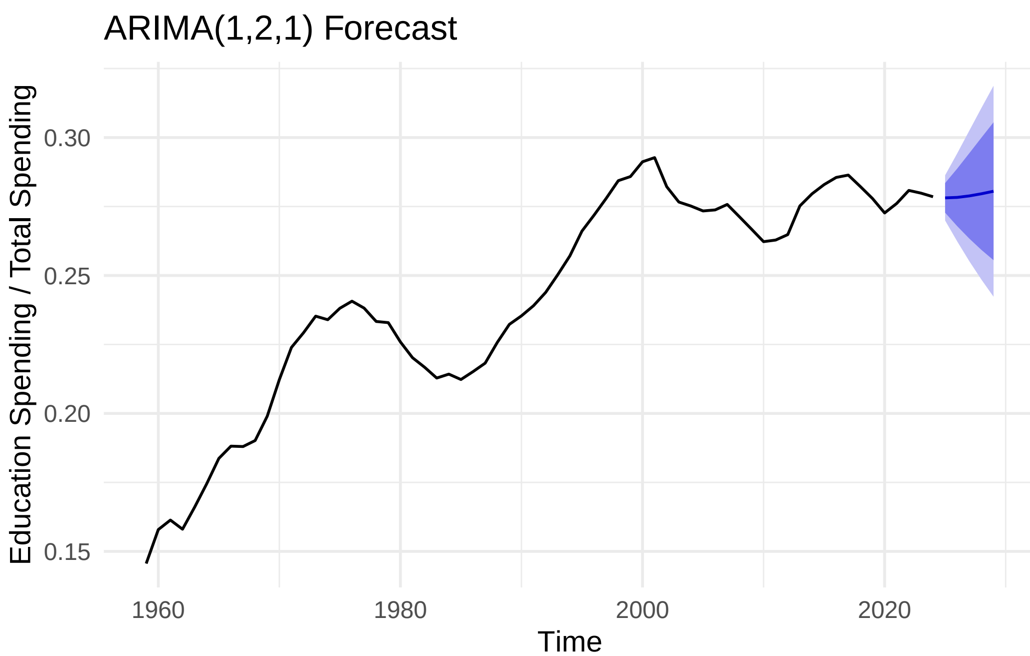
```
                       ME       RMSE        MAE       MPE     MAPE     MASE
Training set 2.102387e-18 0.03897615 0.03281521 -3.129007 14.93651 7.116277
                  ACF1
Training set 0.9371941
```

```
accuracy(drift)
```

```
                        ME        RMSE         MAE       MPE     MAPE      MASE
Training set -1.152887e-17 0.005128775 0.004203824 0.1015114 1.813643 0.9116374
                  ACF1
Training set 0.5933769
```

Furthermore, both models beats the benchmark models. Either model seems like a good choice. Lets plot the ARIMA(1,1,0) model since it is simpler.

```
# Generate the forecast
forecast_result1 <- forecast(fit1, h = 5)

# Plot the forecast
autoplot(forecast_result1) +
  labs(title = "ARIMA(1,2,1) Forecast",
       x = "Time",
       y = "Education Spending / Total Spending") +
  theme_minimal()
```



This forecast suggests that education spending relative to total spending will continue to increase slightly over time.

Conclusion

These analyses imply that that despite the government spending more on education relative to other spending over time, people believe that education should be prioritized more. One possibility is that government spending on education is being misused and isn't have as big of an effect on the quality of education as it should. Another possibility is that government spending in general hasn't been increasing as much as it should so even if the portion of spending that is being used for education increases, the actual amount being spent isn't meeting the demand.